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“Satellite Image Analysis for Agricultural Applications”

Ph.D Workplan

Submitted to

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Abstract:

Satellite image analysis is widely used all over the world for different applications such as geographic studies, disaster estimation and management, crop identification, defence applications, land cover and change identification, identification of water bodies and glacier etc. Optical imagery and Synthetic Aperture Radar (SAR) imagery are available from the satellites. These imageries are used according to application demand.

Crop identification requires images with spatial resolution maximum up to 36.2m to get good accuracy. Landsat-8 with spatial resolution 30m will be suitable for such applications. Landsat gives optical imagery which may not be useful in summer or if the environment is cloudy for crop identification. The alternative is Sentinel satellite image data (SAR imagery with 10m spatial resolution).

Image labelling is second important part of the work as it is required for training purpose. Labelling of the satellite images requires authentic ground truth. Which is only possible by actual periodic visit to the field.

Different classification techniques are available for classification in satellite image processing. Out of which Support Vector Machine (SVM) and Random Forest (RF) have been mostly used for satellite image classification. From last few years, Deep Learning (DL) concept is getting popular in satellite image processing as it is giving better accuracy as compared to available classifiers.

Four level of architecture is referred for identification of crop from satellite images i.e. pre-processing, supervised classification, post-processing and geospatial analysis. Most popular method for pre-processing is self-organizing Kohonen maps (SOMs). Convolution Neural Network (CNN) is popular in Deep Learning (DL). 1-D CNN and 2-D CNN can be applied for exploration of spectral features and spatial features respectively.

Different classification strategies will be developed for crop identification on the same data and will be compared with existing methods in order to justify the use of DL. Kappa coefficient will be used for the accuracy calculations.

Land records are available with the Government. Those land records if mapped, it is possible to identify the owner of the crop. Imagery with different growth stages of the crop will be available in the database. It is also possible to monitor the health of the crop and to decide about drought condition.

This work will be useful for government to keep a record of the individual farmer and his crop conditions.

1. Introduction:

Satellite imagery is widely used for different applications nowadays such as for identification of different objects, defence, disaster management, development and planning, study forestry and environment etc. Still, there are many places we can increase the use of satellite image analysis and improve authentication in presently available systems. In agricultural applications crop identification is an important issue. If we differentiate crops and land cover with maximum accuracy, it would help Government as well as farmers in many ways. Crop health analysis by satellite images is again one of the challenges. Disaster management in draught can be possible if crop health is monitored.

2. Review of Literature and Development:

Multi-temporal multisource satellite imagery in different crop growth stages is required to discriminate different crops [1]. Multispectral optical imagery is not sufficient in summer heterogeneous environment for discrimination amongst crops. For this, Synthetic Aperture Radar (SAR) imagery is suitable [5], [6]. Each crop is having a unique appearance, pattern or spectral signature on the image, but separating these species is again challenging because of variation in soil properties, fertilization, pest conditions, different planting dates, intercropping and irrigation, [4]. Inclusion of shortwave infrared (SWIR) band with visible red (R), visible green (G), and visible blue (B) bands improves results of classification considerably in the identification of crop [3].

Sujay Datta (1991) used LISS-I and LISS-II (Sensors) of IRS-1B Satellite. For classifications, they have used methods maximum likelihood (ML) and minimum distance to mean (MDM). LISS-II (spatial resolution 36.25m) gives better accuracy than LISS-I (spatial resolution 72.6m) [2]. Image with spatial resolution 10m, 20m and 30m don't make a comparable difference [3].

Support vector machine (SVM) and Maximum likelihood (ML) give good results compared with other classification methods like minimum distance, Mahalanobis distance etc. [3]. There are two methods for classification, SVM and Random Forest (RF) are popularly used. But SVM is too much resource consuming to be used for big data and large area. For RF multiple features to be energised [1]. So for satellite image processing application i.e. crop identification of big area with a great accuracy above two methods are not suitable.

Deep Learning (DL) is powerful state of art for image processing including Remote-sensing images. Over past few years, the most popular and efficient approach for multisensor and multitemporal land cover classifications are ensemble-based and deep learning (DL) [1].

In most of the studies, single satellite image is used for classification e.g. land cover or object detection. However, multitemporal satellite images are required for to reliably identify crop type [1].

3. Objectives of Proposed Research:

Work objectives are set mostly for agricultural applications.

1. Discrimination between agricultural and non-agricultural land.
2. Identification of the different crops.
3. Compare different classification strategies with Deep Learning.
4. Recommend an optimum or best suitable method for crop identification i.e. with the best accuracy.
5. Recommend the best imagery for crop identification (Optical/SAR).
6. Land versus crop mapping.
7. Crop health monitoring.
8. Drought area identification.

4. Methodology to be adopted:

First Task in the work is to collect authentic satellite image data i.e. with suitable resolution and from the authentic agency. Spatial resolution 30m of satellite images are suitable for proper crop identification. Multi-temporal and multisensory imagery is required, because optical imagery may not be suitable for identification of crops when the environment is cloudy and in summer. SAR imagery is suitable for the cloudy and heterogeneous environment.

By considering all above requirements, we started collecting data from two satellites: Landsat-8 (optical imagery with spatial resolution 30m) and Sentinel-1A (SAR imagery with spatial resolution 10m).

Training of the data is second important and crucial task of the work. For training, there is a requirement of proper and authentic labelling of the satellite image data. This labelling is only possible by an actual agricultural field visit.

Kappa Coefficient (k) is measured between the classified image and the reference image/map. k tests the argument for each matrix based on the difference between the actual agreement of the classification with respect to reference data and the chance agreement which is indicated by the row and column marginal of the error matrix. Hudson and Ramm (1987) defined the kappa coefficient as:

$$k = \frac{\mathrm{N}\sum_{i=1}^{r} e_{ii} - \sum_{i=1}^{r} e_{i+} * e_{+i}}{N^2 - \sum_{i=1}^{r} e_{i+} * e_{+i}}$$

Where r = number of rows in the matrix; N = total number of elements in the matrix; e_{ii}= number of observations in row i and column i; e_{i+}= marginal total of column i; e_{+i} = marginal total of row i.

As deep learning provides good accuracy for satellite image processing we prefer to use CNN as a classifier for our work by comparing its accuracy with other classifiers.

A four-level architecture is recommended for classification of the crop for multitemporal satellite imagery i.e. pre-processing, supervised classification, post-processing, geospatial analysis as shown in fig.(1) [1].

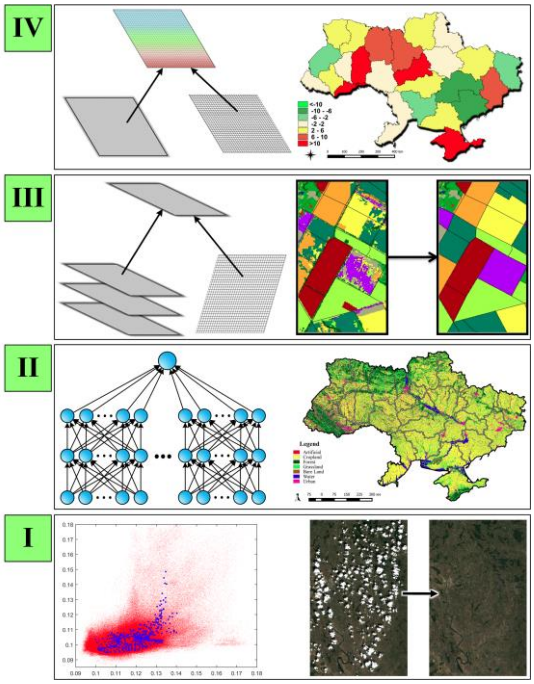

Fig.(1): Four Four-level hierarchical DL model for satellite data classification and land cover/land use changes analysis (I-preprocessing for dealing with missing data on optical images due to clouds/shadows; II-supervised classification; III-postprocessing using additional geospatial data to improve classification maps; IV-geospatial analysis for a high-level product, e.g., crop area estimation).

4.1. Pre-processing:

Optical imagery is contaminated with cloud and shadows and hence pre-processing is required. In satellite image processing one of the most popular methods is self-organizing Kohonen maps (SOMs) in which image segmentation and subsequent restoration of missing data in time series of satellite imagery are done [1].

4.2. Supervised Classification:

Two different Convolution Neural Network (CNN) architectures are proposed i.e. 1-D CNN to explore spectral features and 2-D CNN to explore spatial feature. In this work, we are going to compare proposed methods with different classifiers like RF, SVM, ML, MDM and Neural Network (NN).

In this work proposed Rectified linear unit (ReLu) as the activation function. ReLu is one of the most popular and efficient activation function for deep neural networks. ReLu function is faster and more effective for training CNN comparing to a sigmoidal function.

4.3. Post Processing:

To improve the quality of the result map we require to develop filtering algorithms based on available information on the quality of input data and field boundaries e.g. parcel [10]. Those filters take a pixel-based classification map and specifically designed rules to account for several plots (fields) within the parcel [1].

4.4. Geospatial Analysis:

The final level of data processing provides data fusion with multisource heterogeneous information, in particular, statistical data, vector geospatial data, socio-economic information, and so on. It allows interpreting the classification results, solving applied problems for different domains, and providing the support information for decision makers [1]. For example, classification map coupled with area frame sampling approach can be used to estimate crop areas [18].

Above four level of architecture is useful in identification of crop with good accuracy. Now we need to check land records of the experimentation field. Land records are available with the Government. Those land records if mapped, it is possible to identify the owner of the crop. Imagery with different growth stages of the crop will be available in the database. It is also possible to monitor the health of the crop and to decide about drought condition.

5. Importance of study:

5.1. International status:

As early as 1989, the universal expressive power of three-layer nets was proved via bumps and Fourier ideas [20]. Hinton proposed his deep learning idea in 2006 [21]. A SPOT 5 multispectral image scene covering a 60 km by 60 km area in the Rio Grande Valley of south Texas was acquired on 19 May 2006. Applied different classification methods and estimated percentage accuracy [3]. Space Research Institute of NAS Ukraine and SSA Ukraine (SRI, Ukraine) is actively involved in the Joint Experiment for Crop Assessment and Monitoring (JECAM) activities of the Group on Earth Observations (GEO), and established two JECAM test sites in Ukraine in 2011 [19].

Used Landsat, Radarsat, Sentinel images in Ukraine in 2014. Different combinations of optical and SAR images, as well as SAR modes and polarizations, are assessed for better discrimination of crops [6].

Deep Learning approach is used for classification of satellite images for crop identification using multitemporal and multisensory data in 2017 in Ukraine. The strategy here designed for identification of crop is 1-D and 2-D CNN [1].

5.2. National Status:

Sujay Dutt has done work on accuracy assessment in cotton acreage estimation using Indian remote sensing satellite data in Hisar, Haryana State. In this work, he has used LISS-I and LISS-II sensors of IRS satellite with spatial resolution 72.6m and 36.25m respectively. The accuracy of 36.25m resolution is comparatively better than 76.2m resolution image [2].

Evaluation of RADARSAT Standard Beam data for identification done of potato and rice crops in India by S. Panigrahy in. Five sites, of 10 km=10 km each, were selected within the RADARSAT scene for analysis from the Bardhaman and Hooghli districts of West Bengal state in Eastern India [22].

Currently, lots of ongoing projects are there under National remote sensing Centre (NRSC). Project applications are in the field of Agriculture, Atmosphere and Climate Studies, Development Planning, ISRO Disaster Management Programme, Forestry and Environment, Geology and Mining, Ocean Science, Soil and LU / LC Monitoring, Technology Diffusion and Education, Urban and Infrastructure and Water Resources [23].

5.3. Significance of the study:

1. This work will be significant for identifying different types of crops.
2. Identification of owner of the crop can be possible.
3. It would be possible for the government to keep records of the crop conditions of the farmers without doing actual survey or field visit.
4. Crop health monitoring and estimation of drought can be possible by this work.

6. Proposed Work Plan:

Chapter 1: Introduction and Literature Review

Chapter 2: Pre-processing of the satellite images

Chapter 3: Methodology of the work

Chapter 4: Labelling of the satellite images

Chapter 5: Classification of Images for crop Identification by using CNN

Chapter 6: Comparison of CNN and other Classification techniques

Chapter 7: Land and Crop Mapping

Chapter 8: Crop Health analysis and Drought estimation

Chapter 9: Results, Conclusion and Future scope

7. Year wise Plan of work and target to be achieved:

Year	Work Description	Cumulative completion of work (%)
2017-2018	➢ Literature Survey	5
	➢ Collection of Satellite Images	10
	➢ Field Survey for Ground Truth	15
	➢ Labelling of the data	25
	➢ Design of Proposed method	35
2018-2019	➢ Training and Apply CNN for crop Identification	40
	➢ Determine of accuracy by applying CNN	50
	➢ Classify data by different classifiers like SVM, NN, ML, RF, MDM etc.	60
	➢ Compare proposed method with existing methods.	65
2019-2020	➢ Map Land and Crop according to land records	70
	➢ Crop health identification	80
	➢ Drought Estimation	85
	➢ Publication	90
	➢ Report Writing and Work submission	100

8. Expected outcome:

It is expected from the research work that:

1. This work would be useful to decide which satellite resolution is suitable for crop identification.
2. Which is a best suitable method for classification in satellite image analysis and particular to the crop identification problem.
3. Whether optical imagery is suitable or SAR imagery for crop identification.
4. We should be able to map between agricultural land and crop by using land records.
5. We should be able to monitor the health of the crop and estimation of drought can be possible.

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